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APPLICATION OF FUZZY LOGIC IN THE CONTROL OF POLYMERIZATION REACTORS

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Abstract. Polymer reactors are ideal candidates for the application of fuzzy control. Many polymerization reactions are difficult to model, process measurements are often only available from laboratory analysis at infrequent time intervals and trace impurities can have a marked effect on the reaction. All these factors are manifested in changing polymer properties, which makes control, using a conventional approach, difficult. Over the years, however, process operators have developed the ability to control the reactors under varying conditions. This article outlines how this experience was used in the development of a fuzzy control strategy, and the manner in which feedforward control was incorporated into the design. It also addresses the problem of tuning fuzzy controllers and describes some of the implementation difficulties.

Keywords. Fuzzy control; artificial intelligence; computer control; polymer reactors; rubber industry

INTRODUCTION

Fuzzy control is a technique developed by Lotfi Zadeh (1965, 1968) at the University of California. It represents a mathematical way of looking at vagueness in a form that a computer can deal with. This approach is called fuzzy logic, and it is applied in washing machines, video cameras and many other products (Sangalli, 1992; Omron, 1991). In addition, fuzzy logic has now found applications in the medical field, stock market predictions and various industries, e.g. in the control of cement kilns (Holmblad and Oostergaard, 1982) and paper making machines (Fang-Can, 1986).

Control technology is now developed to a point where it is relatively simple to solve even the most complex control problem, provided it is well-defined. If, however, the process is non-linear, measurements are available infrequently and process dynamics change with time, a more realistic, and more complex problem exists. In such a case a simple solution is not available. Examples of the latter type of problems are found in the operation of cement kilns and some types of polymerization reactions.

Non-linear models can be used in techniques such

as predictive control (van Hoof et al, 1989).

However, if the process behaviour changes in time, the algorithm has to be made adaptive or filtering has to be applied in the feedback path to suppress process/model mismatch and ensure controller stability at the expense of controller performance. For time-varying processes one could use a self-tuning controller. However, if the measurements are not always equi-spaced and if they are available at low frequencies, say once an hour, the self-tuner algorithm will adjust its parameters too slowly or might not even converge.

There is, therefore, a class of control problems in industry for which conventional control technology does not offer a 'quick fix': processes which change in time and which are sampled infrequently.

In many cases operators have developed their own 'rules of thumb' to control these processes. These rules are often based on vague concepts. For example, if the measurement goes up by a small amount and the temperature stays more or less constant, then make a small positive adjustment to the manipulated variable. It is evident that this is not a very well-defined action: there are many vague descriptions such as 'small', 'more or less constant', etc.

Whereas mathematical modelling is based on exact

descriptions, the process operator thinks and acts according to these vague concepts. Fuzzy logic, as developed by Zadeh, enables us to work with these concepts or linguistic expressions. It allows us to develop a computer program that will emulate the actions of the most experienced operator in the control room.

An area that lends itself to the application of fuzzy logic is polymerization reactors. Modelling of many polymerization reactions is often difficult, or, if it can be done, the model may be so complex that it is not practical for implementation on a process computer.

In addition, polymerization kinetics may be heavily influenced by trace impurities, making adequate modelling even more of a challenge. Infrequent off-line sampling rules out the use of any self tuner.

This article will outline in detail how fuzzy logic was applied and how it significantly improved plant performance.

BUILDING BLOCKS OF FUZZY LOGIC

This section describes the building blocks of the fuzzy logic approach, namely the definition of the rule set or production rules (fuzzy inference) and of the membership functions.

'Fuzzy inference' is the reasoning method using fuzzy logic theory, whereby human knowledge is expressed using linguistic rules (or production rules). There are several types of rules, all having the general format:

IF (CONDITION) THEN (ACTION)

The condition or premise could include 'AND' and/or 'OR' connectives, e.g.

IF (TEMPERATURE = HIGH .AND. PRESSURE = RISING SLOWLY) THEN
(OPEN BYPASS VALVE BY A SMALL AMOUNT)

or

IF (DISTANCE TO OTHER CAR = SHORT .AND. SPEED = HIGH) THEN
(BRAKE HARD)

The linguistic expressions 'HIGH', 'RISING SLOWLY', 'A LITTLE', 'SHORT', 'HIGH' and 'HARD' have a certain degree of vagueness or fuzziness. This fuzziness can be described by membership curves or membership functions which can assume different shapes, e.g. straight lines, bell-curved, and so forth.

If a condition is true, the measure of fulfillment of the condition is one and the membership is equal to one. On the other hand, if the condition is false,

both the measure of fulfillment and the degree of membership are zero. However, any value between 0 and 1 is possible (fuzzy sets). Unlike ordinary sets, fuzzy sets have borders which are not distinctly defined.

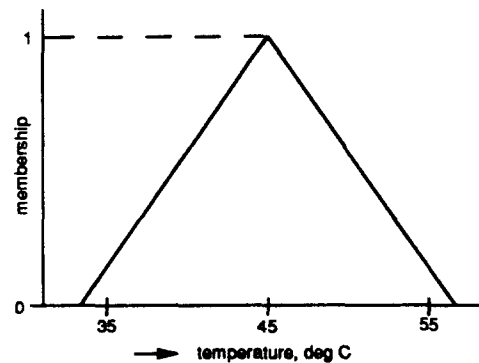


Fig. 1. Membership function for 'warm'.

For example, a 'warm' shower means different things to different people. Everybody has their own interpretation of 'warm'. The membership function could look as shown in Figure 1. This function does not have to consist of straight lines nor does it have to be symmetrical.

How does the inference engine arrive at a final result if there are several rules active? This is graphically illustrated in Figure 2.

Assume that membership curves have been defined as shown and that there are two active rules:

RULE 1: IF ($X_1 = \text{SP}$.AND. $X_2 = \text{LP}$)
THEN $\Delta U = \text{LP}$

RULE 2: IF ($X_1 = \text{ZE}$.AND. $X_2 = \text{SP}$)
THEN $\Delta U = \text{SP}$

where X_1 = deviation of temperature from setpoint, X_2 = deviation of pressure from setpoint, ΔU = incremental action to the bypass valve, SP = small positive membership, ZE = insignificant membership and LP = large positive membership.

The calculation of the final result or adjustment can be done in several different ways. A method that is often used is the 'gravity principle'. The summed areas of the fuzzy sets are divided in two. In other words, the centre of gravity is determined. A slightly different method which gives virtually the same result but which is computationally easier to realize, is the 'weighted individual membership' method. In this method the centre of gravity for each output membership is defined by the user, let it be C_i . For a particular output membership function (e.g. SP, LP,...), C_i represents the change to the manipulated variable, as defined by the user, for which the membership function is one hundred percent. If the membership of a particular rule is μ_i then the final action is calculated according to:

$$\Delta u = \sum_i \mu_i C_i / \sum_i \mu_i \quad (1)$$

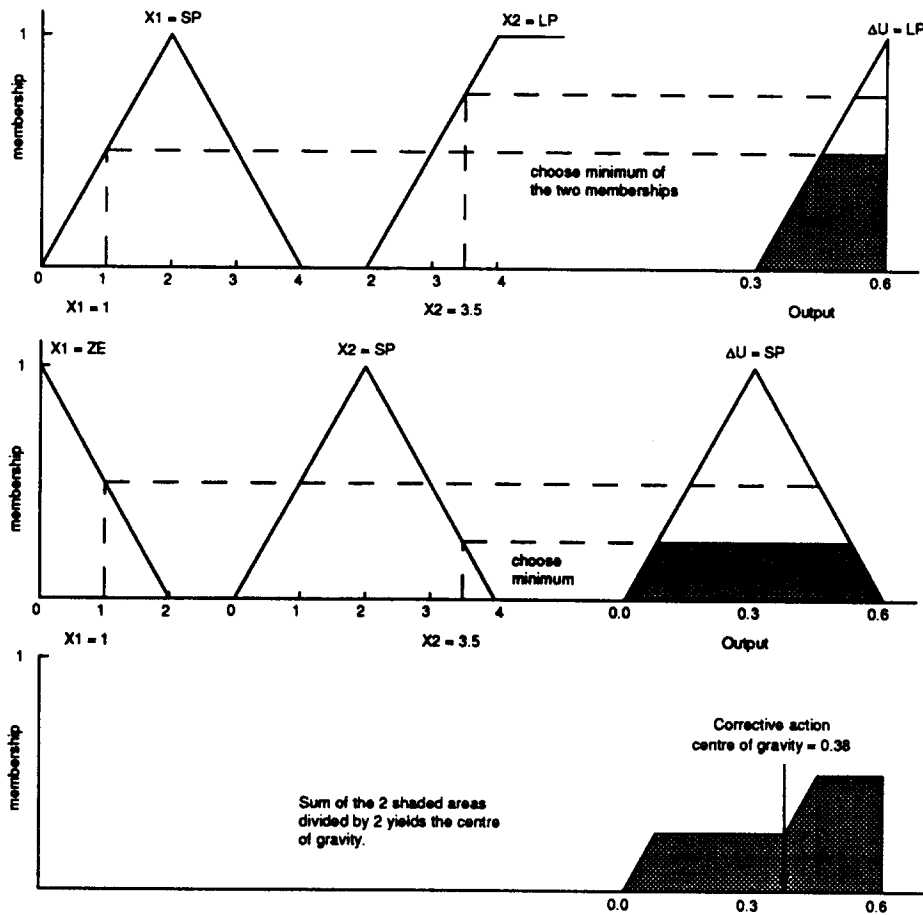


Fig. 2. Fuzzy Inference Action for Two Rules

where

Δu = final action to be taken

μ_i = membership of rule i

C_i = centre of gravity of the membership set.

The result can best be illustrated using an example. If for Figure 2 $\mu_1(\text{SP})=0.50$ and $\mu_2(\text{LP})=0.75$ then from rule one the output membership is obtained as the minimum of the two input memberships, hence $\mu(\text{LP})=0.50$. Similarly, if $\mu_1(\text{ZE})=0.50$ and $\mu_2(\text{SP})=0.25$ then the output membership $\mu(\text{SP})=0.25$. If now $C(\text{SP})=0.3$ and $C(\text{LP})=0.5$, then

$$\Delta u = \frac{0.5 \cdot 0.5 + 0.25 \cdot 0.3}{0.75} = 0.43 \quad (2)$$

The fuzzy control procedure can now be summarized as follows:

- Express the operator experience in the form of rules using linguistic expressions. Example: if the deviation of temperature from setpoint (error) is small positive and the deviation of pressure from setpoint is large positive then make a large positive adjustment to the bypass flow.
- Determine the membership functions for the input variables and the output variables, e.g., temperature error = {MP, SP, ZE, SN, MN}; pressure error = {SP, ZE, SN}; where MP = medium positive, SP = small positive, ZE = zero, SN = small negative and MN = medium negative.
- Convert the rules into mathematical expressions, using the defined membership functions, e.g. the previous rule is now written as:
IF ($X_1 = \text{SP}$.AND. $X_2 = \text{LP}$) THEN ($\Delta u = \text{LP}$).
- Once the rules and membership functions are defined, measurements of temperature

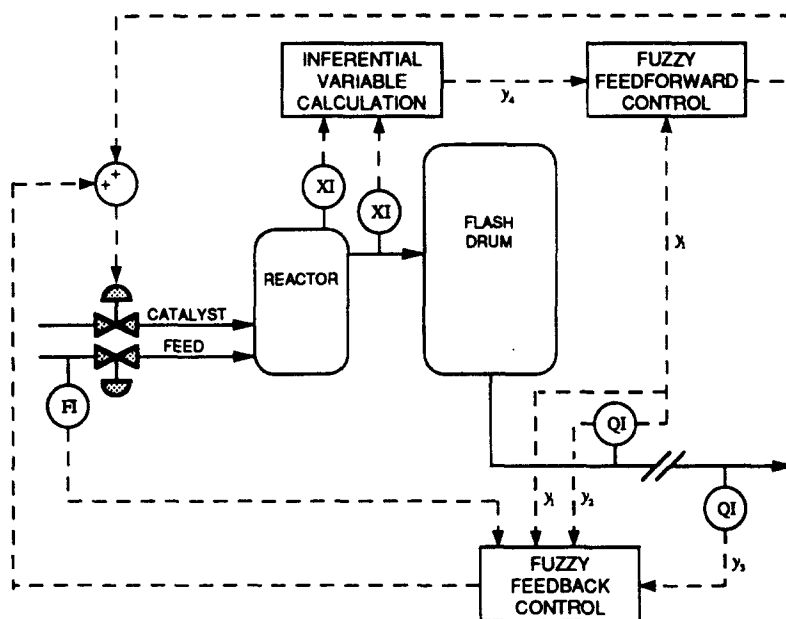


Fig. 3. Polymerization Process

and pressure will produce an active rule set for the output Δu and a final adjustment can be calculated using equation 1.

5. Repeat the calculation of the adjustment at regular intervals.

A POLYMERIZATION PROCESS

The polymerization reactor considered here is a continuous stirred tank reactor into which monomers and catalyst are being fed, the catalyst flow being the control variable.

The polymer is formed and withdrawn from a flashdrum, where unreacted components are flashed off for reuse after purification and separation. Polymer samples are taken every hour and analyzed by the laboratory personnel. The polymer properties are the controlled variable. The process is described in more detail in the literature (Kirk-Othmer, 1979; Roffel and Chin, 1989).

The process operator bases his decision for making an adjustment in the catalyst flow on four process variables. One of these process variables is an inferential variable, calculated from two reactor measurements. The reactor system is shown in Figure 3. For variables y_1 , y_2 and y_4 the following linguistic expressions were defined: 'LP', 'SP', 'NC', 'SN' and 'LN', representing 'large positive', 'small positive', 'no change', 'small negative' and 'large negative'. For process measurement y_3 three sets were adequate: 'P', 'NC' and 'N', representing 'positive', 'no change' and 'negative'. If all four variables were to be integrated into one fuzzy control programme, we could have a maximum of $5 \times 5 \times 3 \times 5 = 375$ rules initially.

Some of these rules would probably never be active and could, consequently, be deleted from the rule set. However, the number of rules might still be fairly large. Therefore, the rule set was subdivided into two sets: one using the off-line measurements y_1 , y_2 and y_3 , which is called the fuzzy feedback control system, and one which uses the inferential variable y_4 and off-line measurement y_1 in a feedforward strategy.

By separating the rule set into two, we reduced the number of possible combinations from 375 to $5 \times 5 \times 3 + 5 \times 5 = 100$. The number of 100 can be further reduced since some of the rules are never active. An additional advantage is that the feedforward rule set can now run at a higher frequency than the feedback rule set.

IS IT WORTH THE FUZZ?

Is fuzzy control just another marketing tool for a product that achieves what another product could achieve? In the literature (Yamakawa, 1989) one encounters an example where the angle and angular velocity for a small vehicle are measured with a rigid pole joined to it by a pivot. If the desired position of the pole is vertical (angle zero degrees), then the angle represents the current error (setpoint - process measurement) and the angular velocity the rate of change, which equals the current error minus the previous error. Thus, we encounter the two terms of the well-known proportional-integral controller. The question is then, would a PI controller not perform equally well? The answer is: maybe. But the process is nonlinear, requiring a nonlinear PI controller. Furthermore, if the process required an asymmetric

controller, fuzzy logic could easily accommodate it. An important advantage of fuzzy logic is the ease with which multiple measurements can be integrated into the control scheme. Most conventional controllers act on a single process input (error in various forms), whereas the fuzzy controller can accommodate multiple inputs, in order to calculate what control action to take. No other approach could have integrated that many variables into a control scheme that elegantly.

TUNING THE FUZZY CONTROLLER

One of the most difficult tasks for the engineer is to ensure that he gets information from the process operator that is complete. In our design, we interviewed only the most experienced operator to define the rule set. Once the rule is defined, the membership functions have to be established. In our case we had to define $5+5+5+3 = 18$ membership functions for the input, and 5 membership functions for the output (LP, SP, NC, SN, LN). Hence, there is a total of 23 membership functions affecting the final result.

In defining the membership functions we interviewed more than one operator. This way we would use reasonable average values for the classification of what constitutes 'large positive', 'small positive' and so forth. Different operators tend to make different adjustments. Once the membership functions were defined, we put the fuzzy controller online, in an advisory mode for a period of two weeks. During this time the operators would record all the process adjustments they made and all the information the fuzzy control system provided. These included rules fired, membership of the active rules, recommended control action, etc. At the end of this period the results were evaluated and the rule set, as well as some of the membership functions were modified accordingly. After the two week period the control program was put online and some further tuning was required. At this point only adjustments to the output membership functions were made without altering any of the rules or input membership functions. Also, when the fuzzy control system was implemented on similar polymer reactors in other plants we found it sufficient to adjust the output membership functions only.

DIFFERENCE BETWEEN FUZZY AND CONVENTIONAL FEEDFORWARD CONTROL

The function of conventional feedforward control is to eliminate disturbances before they affect the process output. Whether the disturbance is positive or negative is irrelevant, for the same size of the disturbance, the magnitude of the feedforward action will be the same.

Fuzzy feedforward control offers greater flexibility and we can use this to enhance control. The inferential variable y_4 showed a relationship with the final product quality y_3 : if y_4 would increase, y_3 would usually increase and if y_4 decreases so would y_3 .

If the controlled variable is below setpoint and inferential variable is increasing, one could expect that the controlled variable is moving towards the setpoint, therefore little action might be necessary. In addition, if the controlled variable is above setpoint and the inferential variable is increasing, a major process adjustment has to be made since the controlled variable is moving even further away from setpoint. Conventional feedforward control would only look at the change in the inferential measurement and make an adjustment to the process. Fuzzy feedforward can be made more intelligent in that it decides whether the disturbance will have a significant impact on the controlled variable. The control action in case of fuzzy feedforward is therefore quite different from the conventional feedforward case.

VARIABLE DEAD TIME COMPENSATION

A slight oscillatory behaviour in the control and controlled variable would occur at times, especially after a large reduction in the feed to the reactor. After analyzing this problem it was found that the process dynamics changed substantially during a major feed change. The fuzzy inference engine was designed for average conditions and could handle feedcuts up to 20 percent. In order to account for major changes, the following modification was made to the control law:

$$\Delta u_{impl}(k) = \Delta u_{calc}(k) - \alpha \Delta u_{impl}(k-1) \quad (3)$$

where Δu_{calc} is the adjustment calculated by the fuzzy inference engine at time k and Δu_{impl} the implemented control action.

At large reactor feedrates α was equal to zero, α would be positive for small feedrates. A linear relationship between α and the feedrate was sufficient to eliminate the oscillatory behaviour. What the control law effectively did was to adjust the corrective action based on added dead time and increased process time constant.

The problem of the varying sampling time was addressed in a similar manner.

FINAL STRUCTURE OF THE CONTROL PROGRAMME

The final control programme consists of a number of modules operating in series. The programmes run in a TDC3000 application module and even though this may not be the ideal programming

environment for this type of application, no problems were encountered. The following modules were designed:

1. Module one collects the field measurements $y_1 \dots y_4$, validates them and calculates the type (e.g. for y_1 {LP, SP, NC, SN, LN}) and degree of the membership.
2. Module two determines whether the off-line measurements y_2 and y_3 have updated. If not, a flag is set to indicate that only feedforward control should be executed.
3. Module three is the inference engine, which will determine which rules should be fired. It also determines the active output rule type (LP, SP, NC, SN, LN) and the degree of membership.
4. Module four calculates the uncorrected process adjustment using the weighted individual memberships method (eqn. 1).
5. The last module compensates for varying reactor feed and sampling time. It calculates the corrected process adjustment and validates it against high and low limits and the rate of change limitation.

CONCLUSION

Fuzzy control of the polymerization reactor has been extremely successful and has succeeded where conventional control methods failed. Improvements in the plant performance factor (Ppk) in the order of 0.3-0.6 have been achieved. The application of fuzzy logic was appropriate because an adequately detailed model for the polymerization process did not exist and would be very time consuming to derive if at all possible. The process had non-linear characteristics, time-varying behaviour and a low and varying sampling frequency.

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